



Spatial yield estimates of fast-growing willow plantations for energy based on climatic variables in northern Europe

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Abstract

Spatially accurate and reliable estimates from fast-growing plantations are a key factor for planning energy supply. This study aimed to estimate the yield of biomass from short rotation willow plantations in northern Europe. The data were based on harvesting records from 1790 commercial plantations in Sweden, grouped into three ad hoc categories: low, middle and high performance. The predictors included climatic variables, allowing the spatial extrapolation to nearby countries. The modeling and spatialization of the estimates used boosted regression trees, a method based on machine learning. The average RMSE for the final models selected was 0.33, 0.39 and 1.91 (corresponding to $R^2 = 0.77, 0.88$ and 0.45), for the low, medium and high performance categories, respectively. The models were then applied to obtain 1×1 km yield estimates in the rest of Sweden, as well as for Norway, Denmark, Finland, Estonia, Latvia, Lithuania and the Baltic coast of Germany and Poland. The results demonstrated a large regional variation. For the first rotation under high performance conditions, the country averages were as follows: >7 odt $\text{ha}^{-1} \text{yr}^{-1}$ in the Baltic coast of Germany, >6 odt $\text{ha}^{-1} \text{yr}^{-1}$ in Denmark, >5 odt $\text{ha}^{-1} \text{yr}^{-1}$ in the Baltic coast of Poland and between $4\text{--}5$ odt $\text{ha}^{-1} \text{yr}^{-1}$ in the rest. The results of this approach indicate that they can provide faster and more accurate predictions than previous modeling approaches and can offer interesting possibilities in the field of yield modeling.

Keywords: bioenergy, biofuels, biomass, boosted regression trees, climatic restrictions, energy crops, predictive models, short rotation, willow, yield maps

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Introduction

How much biomass can be produced from fast-growing plantations in a given area? Fast-growing plantations are an alternative feedstock of wood biomass for the emerging energy sector and related industries. Such plantations are based on fast-growing woody species (such as willow) generally established on agricultural land, being intensively managed. The expected life span of a willow plantation is considered to be about 25 years, and the same plantation can be harvested several times, with rotations (*cutting cycles*) from 3 to 6 years (e.g., Rahman *et al.*, 2014).

At present, Sweden provides a good basis for commercial experience: fast-growing willow plantations have been cultivated at commercial level since the 1980s, particularly willow, making Sweden the leader in

Europe both in long-term experience and total area planted, which entails c. 13 000–16 000 ha (Mola-Yudego & González-Olabarria, 2010). In addition, Denmark currently entails 5700 ha (Jørgensen *et al.*, 2014), England c. 2500 ha (DEFRA, 2014) and Germany c. 4000–5000 ha (Wühlisch, 2012), whereas there are ambitious goals for their expansion, for example: Poland, aiming at 170 000 ha to be planted with energy crops (Kunikowski *et al.*, 2005), or UK, planning 350 000 ha by 2020 (DEFRA, 2007), although these levels of ambition may be subject to changes, as the Swedish example shows (Mola-Yudego & González-Olabarria, 2010).

Planning the expansion of these plantations requires accurate and updated information concerning both current and potential yield, a prerequisite for a successful development of bioenergy markets based on energy crops (Mola-Yudego *et al.*, 2014). At local level, productivity estimates are required for planning wood fuel supply chains, for the location of bioenergy plants (e.g., Mola-Yudego & Pelkonen, 2011), for profitability

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analysis (e.g., Toivonen & Tahvanainen, 1998; Rosenqvist & Dawson, 2005; Dimitriou & Rosenqvist, 2011) and for the general logistics and management associated to biofuels, among others. At national level, productivity estimates are needed for the construction of scenarios (e.g., Bauen *et al.*, 2010), for the implementation of policy incentives (e.g., Mola-Yudego & Pelkonen, 2008), or even for environmental assessment (e.g., Gonzalez-Garcia *et al.*, 2012), among others.

Methods to predict plantation productivity have been traditionally based on regression models, where yield was predicted as a function of different parameters, following pre-established equations. To address the spatial component necessary to predict potential yield in different areas, these parameters have been often related to climate. Indeed, temperature and precipitation have been considered the most important factors for the growth of willow plantations (Perttu, 1999), and several of the initial studies on willow plantation growth have modeled yields based on climatic variables (e.g., Nilsson & Eckersten, 1983; Perttu *et al.*, 1984). Also climate-based models were used in Sweden to model the potential productivity at spatial level of willow plantations (Lindroth & Båth, 1999), resulting in productivity maps based on the linear relationship between yield and precipitation during the growing season.

However, these methods present several modeling limitations, as in many cases, the relationships between the variables used as predictors are complex, presenting several interactions, and the use of predefined relations (i.e., linear regression) can lose predictive power. More recent approaches have considered the inherent spatial component of yield prediction, using more ambitious modeling techniques. Aylott *et al.* (2008) produced estimates based on partial least squares, aiming at mapping the plantations productivity in UK. In this case, the modeling approach required detailed data of each plantation's growth and management activities, which were obtained from a network of well-studied experimental trials. Mola-Yudego (2010) produced estimates based on *k-nn* imputation methods (see, e.g., Kilkki & Päivinen, 1987; Muinonen & Tokola, 1990; Tomppo, 1990; Tokola *et al.*, 1996), aiming at mapping the plantations' productivity in Sweden. Following this approach, the variables from a specific area are predicted as a weighted average of the spectrally closest plantations (which are defined as nearest neighbors, *nn*) and the feature spectrum is defined by a vector of climatic variables. In this case, no detailed data of each plantation's growth were needed, but relied on a large pool of plantations to get stable and accurate estimates. However, the nature of the method makes it difficult to model the specific relations between variables and yields and limits its potential for extrapolation to those areas outside the sampled data.

In this context, the aim of this study was to provide accurate estimates of productivity for fast-growing willow plantations, spatially extrapolating a large sample of Swedish plantations to nearby areas in northern Europe, using climatic data. The results of this approach can be applied, among others, to the policy and economic considerations associated with wood supply derived from energy crops, as well as their future development.

Materials and methods

Description of the data

The data set used in the calculations was based on harvesting records from the first rotation of 1790 willow plantations in central and south Sweden (see Mola-Yudego, 2010). The records therefore correspond to harvest aboveground leafless biomass. The field measurements were provided by Lantmännen Agroenergi AB. Data with inconsistent records (e.g., missing digits in the coordinates) or lacking information regarding the area planted or the location were excluded from the data set. All plots were georeferenced to a 1 km precision. The average yield was calculated by dividing the total harvested biomass by area planted and the number of years of the rotation. The plantations were cut after the first growing season after planting to promote sprouting (*cutback*). The data used included 7753 ha planted during the period 1986–2005 in the area defined from 55°20'N to 61°29'N and from 11°33'E to 18°56'E. The average size of the plantations was 4.3 ha (SD: 4.2 ha).

The climatic data were based on the climate layers calculated for northern Europe (Hijmans *et al.*, 2004; WorldClim database version 1.4). These data consist of a set of grid maps resulting from an interpolation process of temperature and precipitation averages (Hijmans *et al.*, 2005), based on the reference period 1960–1990, to assess the average climatic conditions of the area.

The maps used in this study had a 30-s spatial resolution (which provides ~1 km precision). To link the climatic variables with the ground data, the maps were projected from the originally projected datum into the same coordinate system as the yield data (UTM, zone 33N). The precision of the interpolated climatic variables was 0.1° C for temperature and 1 mm for precipitation. The monthly averages of maximum, mean and minimum temperatures and precipitation (referred as *Tmax*, *Tmean*, *Tmin* and *P*, respectively) were obtained for each plantation.

Statistical modeling approach

The modeling approach was based on boosted regression trees (BRT). This approach combines statistical and machine learning techniques aiming at the improvement of the performance of a single model by fitting many models and combining them for prediction (Schapire, 2003). Besides the selection of the variables to be included in the models, common to any modeling approach, BRT requires additional parameters to be calibrated. BRT models are defined by different parameters: number of

trees, learning rate (or *shrinkage*, related to the reduction of the impact of any additional tree), bag (random fraction of the residuals is selected to build the tree, per iteration) and number of interactions between variables.

The models and statistical analysis were developed in R version 3.2.0 (R development core team, 2014). The BRT models were based on the *dismo* extension of the *GBM* package (Ridgeway, 2006), developed by Elith *et al.* (2008).

The predicted variable was the mean annual growth per hectare, expressed as oven dry tonnes per hectare and year ($\text{odt ha}^{-1} \text{ yr}^{-1}$). Due to the high variability of the yields resulting from different management practices (Mola-Yudego & Aronsson, 2008; Mola-Yudego, 2010), the plantations were classified according to their local performance, using municipalities as a unit of analysis. For each municipality, the plantations were ranked according to their measured yields and then grouped in three categories made of approximately an equal number of plantations (Fig. 1). There were 119 municipalities with data, with an average of 15 plantations each.

The categories were described as follows: *high* performance, *medium* performance and *low* performance (Table 1), corresponding to the upper third of yield level, the middle third and the lower third at each municipality. The average establishment year was 1994 for all three categories. Inside the same municipality, plantations of the category *medium* were established on average +0.09 years (*P*-value: 0.079) more recently than those of the *low*, and plantations of the category *high* were established +0.29 years (*P*-value: 0.622) more recently than those of the *medium* and +0.47 years, (*P*-value: 0.032) more recently than those of the *low*. There were not significant differences concerning the climatic profile between categories in the same municipality.

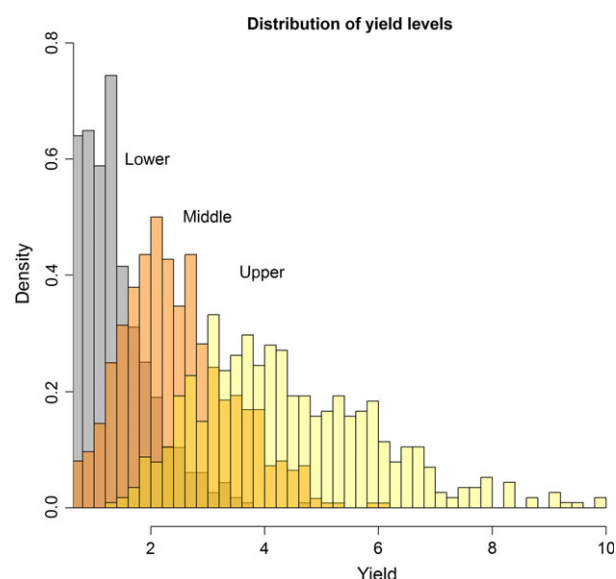


Fig. 1 Distribution of the commercial willow plantations ($n = 1790$) in Sweden used in the models. The groups correspond to a classification of local performance at municipality level: low, middle and high performance. Density refers to the probability density of the counts.

The climatic variables selected as predictors were chosen following Mola-Yudego (2011a). The main criteria were defined to reflect the influence of climatic characteristics on yield based on existing literature, to present minimal bias and minimal root-mean-square error (RMSE) and to avoid excessive multicorrelation. An additional criterion derived from the previous study was to remove variables whose empirical constant p was close to 0 when optimized for prediction (see Mola-Yudego, 2011a,b). A total of six climatic variables were included in the models: $T_{\max 2}$ (February), $T_{\max 7}$ (July), $T_{\max 8}$ (August), $T_{\min 10}$ (Oct), $T_{\text{mean}5}$ (May) and P_{sum} (sum of the precipitation from May to September).

The combination of different number of interactions between the selected variables, the required number of trees, learning rates and bags would result in a large number of potential models. Therefore, several models were tested sequentially, being the learning rates fixed at: 0.02, 0.01, 0.008, 0.005 and 0.001; the bag at: 0.2, 0.5 and 0.8; and the number of interactions at: 1, 2, 4, 6, 8, 10, 12, 14 and 16. The number of trees was obtained through optimization (see Ridgeway, 2006): first the BRT models were built with the default 10-fold cross-validation, and this procedure was used to estimate the optimal number of trees to be included. The final models were finally built on the full data set, using the number of trees identified as optimal. This resulted in 432 models. Among those, the model selection was based on a double criterion: the model should have a high predictive power and should present stable predictions (small variations in the parameters defining the model should not result in markedly different predictions). These two criteria were evaluated through the RMSE (root-mean-squared error of the predictions vs. the observed data) and the RMSD (root-mean-squared deviation), respectively. The RMSD was defined to assess the stability of the predictions: Each model was run in 6500 points generated on agricultural land in northern Europe. Therefore, the RMSD of those predictions was calculated for each model, being defined as follows:

Table 1 Descriptors for the three categories defined. N : number of plantations. N (*municipality*): average number of plantations per municipality. *Yield* refers to the harvested first rotation (cutting cycle). *Year Est.* refers to the year when the plantation was established. *Relative difference* refers to the differences in year of establishment among categories inside the same municipality. Numbers in parenthesis refers to the standard deviations

	Low performance	Medium performance	High performance
N	578	620	592
N (<i>municipality</i>)	4.9	5.2	5.0
Yield ($\text{odt ha}^{-1} \text{ yr}^{-1}$)	1.23 (0.57)	2.47 (0.95)	4.73 (2.45)
Year Est.	1994.1 (2.395)	1994.07 (2.398)	1994.33 (2.583)

$$\text{RMSD} = \sqrt{\frac{\sum (y_i - \bar{y}_i)^2}{n}} \quad (1)$$

where, y_i is a prediction for a point using a given model, \bar{y}_i is the mean of the predictions of all models for point i and n the total number of models considered for each performance category. After the evaluation, prediction maps were produced for northern Europe, in areas geographically and climatically similar to Sweden. The predictions were restricted to those areas defined as agricultural land using the Corine 2000 classification (EEA, 2000), 250 m resolution.

Finally, for each country, an estimate of the average annual productivity for the estimated life span of the plantations was calculated. The calculation was based on Mola-Yudego (2010) where yield estimates for the first cutting cycle are used as a reference value. The cutting cycle length was assumed to be 4 years, and it considered five rotations. The increments of productivity along the rotations were estimated based on Mola-Yudego & Aronsson (2008). The average annual yield was then calculated by dividing the accumulated production by the total number of years of the five rotations, plus one, to include the

initial year for cutback (in total: 21 years); these values were the basis for estimating of the potential energy produced under different percentages of available arable land.

Results

Of the 432 models constructed, 62 could not be calculated, particularly those with high learning rate (0.02), especially when there were many interactions and in the high performance category. In total, 142, 135 and 93 models were considered, for the low, middle and high performing categories (Fig. 2). The results showed that models with few interactions between the variables resulted in low RMSE (Fig. 3). The average RMSE for all the models presented was 0.40, 0.46 and 1.98 (corresponding to $R^2 = 0.64$, 0.75 and 0.36) for the categories of low, medium and high performance, respectively.

In general, the overall performance of the predictions was better for the medium and low productivity planta-

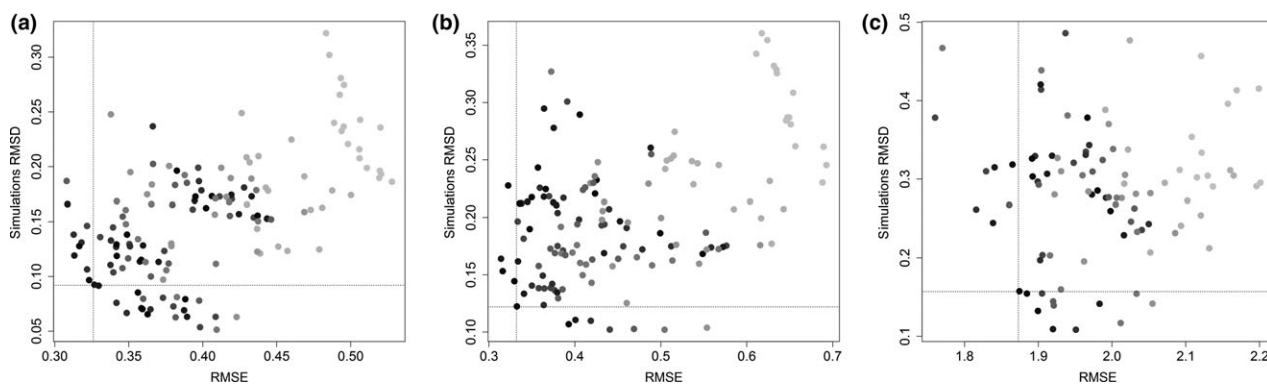


Fig. 2 Performance of the tested models (Root-mean-square error) and stability of the predictions (Root-mean-square deviation). Each point represents the overall results for one model. RMSD is calculated as the root mean squared of the differences in 6500 test points between predictions for a given model and the average predictions from all models. (a) Lowest performance ($n = 142$), (b) middle performance ($n = 135$), (c) highest performance category ($n = 93$). Color gradient: light = 1 interaction, darkest = 16 interactions.

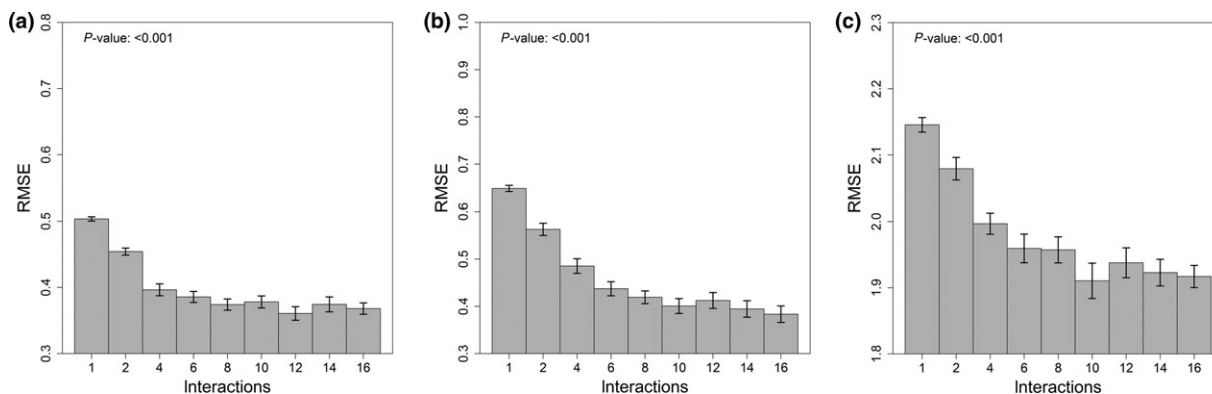


Fig. 3 Root-mean-square error (RMSE) as a function of the number of interactions. (a) Lowest performance, (b) middle performance, (c) highest performance category.

tions. The final models selected included the following: 14 interactions, 0.005 learning rate and 0.5 bag for the low performance; 16 interactions, 0.02 learning rate and 0.5 bag for the medium performance; and 16 interactions, 0.008 learning rate and 0.5 bag for the high performance. The coefficients of determination (R^2) were 0.77, 0.88 and 0.45, respectively (Table 2). The models failed to accurately predict the highest yields of the best performance group, especially above 10 odt ha⁻¹ yr⁻¹ (Fig. 4).

Psum and Tmax in February presented the highest weights in all categories (over 40%), whereas Tmax in August presented the lowest (lower than 10%) (Table 2). Psum presented strong interactions with all the variables related to temperature included in the models. The highest interactions for all categories were between Tmax in February and Psum, and Tmin in October and Psum. In the case of middle performance, an additional

Table 2 Weights for each variable (%), estimates of model's Root-mean-squared error and coefficient of determination (R^2) of the predictions, for every performance group (Low: low performance, Medium: middle performance, High: upper performance)

Variable	Low	Medium	High
Tmax2	24.65	23.87	21.52
Tmax7	14.48	16.45	10.77
Tmax8	8.11	6.61	8.25
Tmin10	14.91	15.05	21.06
Tmean5	14.87	14.68	18.24
Psum	22.95	23.32	20.12
RMSE	0.33	0.33	1.87
R^2	0.77	0.88	0.45

Psum: aggregated precipitation May to September; T, temperature; Max, maximum; Min, minimum, numbers correspond to the calendar months.

strong interaction was between Tmax in July and Psum (Table 3).

The effect of the variables on yield was different for the different variables and performance categories. In general, precipitation had a positive effect on yield, for all performance groups. Tmax in February, Tmean in May and Tmin in October had a positive effect, whereas Tmax in July presented a negative effect. Tmax in August presented a positive effect for the middle performance group (Fig. 5). It must be taken into account

Table 3 Variable interactions, for every performance

Variable	Tmax2	Tmax7	Tmax8	Tmin10	Tmean5	Psum
Low						
Tmax2	0	1.62	0.93	7.3	3.24	6.94
Tmax7	0	0	0.74	0.95	0.96	1.86
Tmax8	0	0	0	0.76	2.01	1.25
Tmin10	0	0	0	0	0.63	5.94
Tmean5	0	0	0	0	0	3.79
Psum	0	0	0	0	0	0
Medium						
Tmax2	0	3.02	1.83	8.74	28.62	30.64
Tmax7	0	0	1.4	2.39	1.83	21.02
Tmax8	0	0	0	5.2	0.82	5.36
Tmin10	0	0	0	0	2.86	6.51
Tmean5	0	0	0	0	0	15.72
Psum	0	0	0	0	0	0
High						
Tmax2	0	5.89	4.78	18.45	17.49	18.28
Tmax7	0	0	4.52	4.75	1.18	5.09
Tmax8	0	0	0	1.7	3.63	2.05
Tmin10	0	0	0	0	3.52	27.19
Tmean5	0	0	0	0	0	9.03
Psum	0	0	0	0	0	0

Psum: aggregated precipitation May to September; T, temperature; Max, maximum; Min, minimum, numbers correspond to the calendar months.

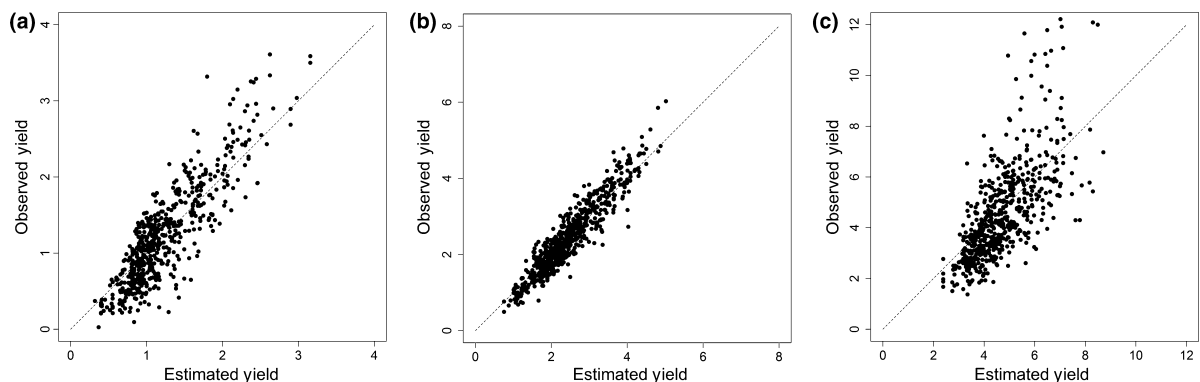


Fig. 4 Measured and predicted yield for the commercial fast growing willow plantations, according to the models. (a) Lowest performance, (b) middle performance, (c) highest performance group.

that the partial dependence is also defined by the interactions among variables (Table 3).

The resulting predictions were aggregated by region and country, to estimate the potential area under different productivity categories (Fig. 6). It must be taken into account that in the northernmost regions, there is scarce agricultural land, often located nearby the coastal areas in the best climatic conditions. This makes the regional averages of Lapland (Finland), Finnmark (Norway) and Upper and Middle Norrland (Sweden) to be high when aggregated at region level, compared to other more southern regions.

The analysis of the stability of the estimates was evaluated through the standard deviation of the predictions of the models for each of 6500 random points (Fig. 7). The models show consistency concerning the predictions in Sweden, Finland, Estonia and most of Latvia. However, small changes in the model parameters resulted in larger differences in the predictions for the Western areas of Jutland (Denmark) as well as the west of Lithuania, and the Eastern parts of Northern Poland, especially concerning the best performance group.

Concerning the best performance category, the mean for the first rotation by country (Fig. 8) ranged from 4.1 odt ha⁻¹ yr⁻¹ (Finland) to 7.1 odt ha⁻¹ yr⁻¹ (Northern Germany). For the whole area, the average for the first rotation for this category was 4.8 odt ha⁻¹ yr⁻¹ (SD 0.98). However, it must be taken into account that there is a strong spatial variability, as most of the countries showed large regional differences (Fig. 9). When considering the 10% agricultural land with the highest willow productivity (1.5×10^6 ha), the average yield for the area studied was 6.5 odt ha⁻¹ yr⁻¹ for the first rotation.

Discussion

This study aims at estimating the spatial distribution of production of biomass for energy from short rotation willow plantations by modeling their potential productivity based on climatic variables. The data were based on harvest records for the first rotation from 1790 commercial plantations for the period 1989–2005, and it has been extensively used in the past for modeling purposes (e.g., Mola-Yudego & Aronsson, 2008; Mola-Yudego,

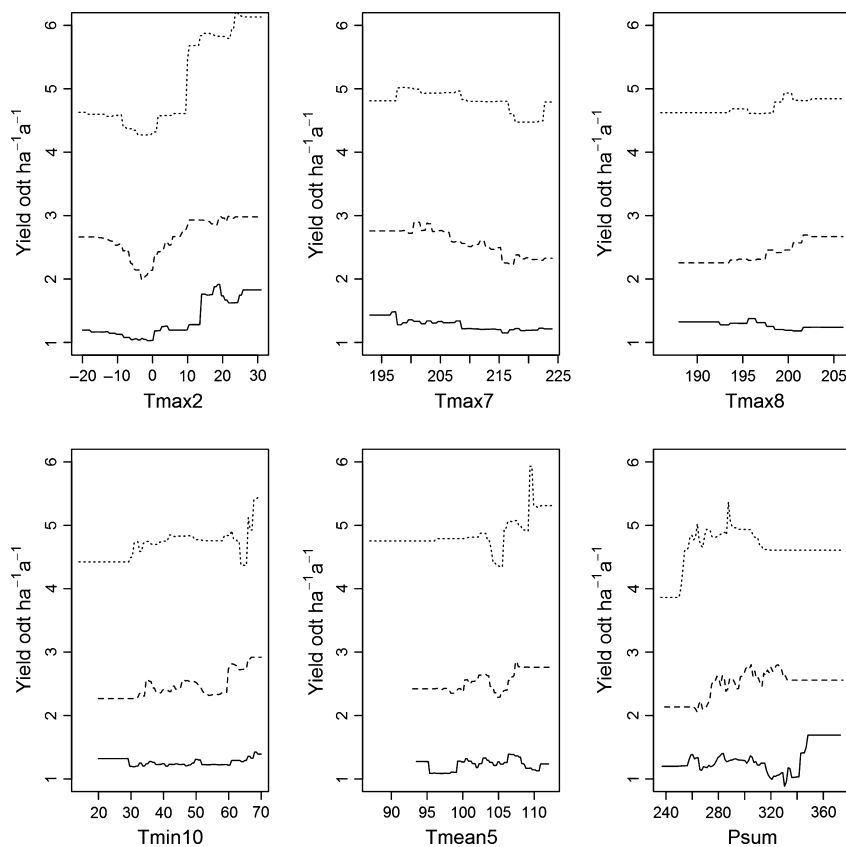


Fig. 5 Partial dependence plots of the predictors in the model, for the performance categories (lower, middle, upper). The temperatures are expressed in degrees Celsius ($\times 10$), and precipitation in mm of rainfall. Yield: average annual harvested yield of willow plantations. Psum: aggregated precipitation May to September, T: Temperature, Max: maximum, Min: minimum, numbers correspond to the calendar months.

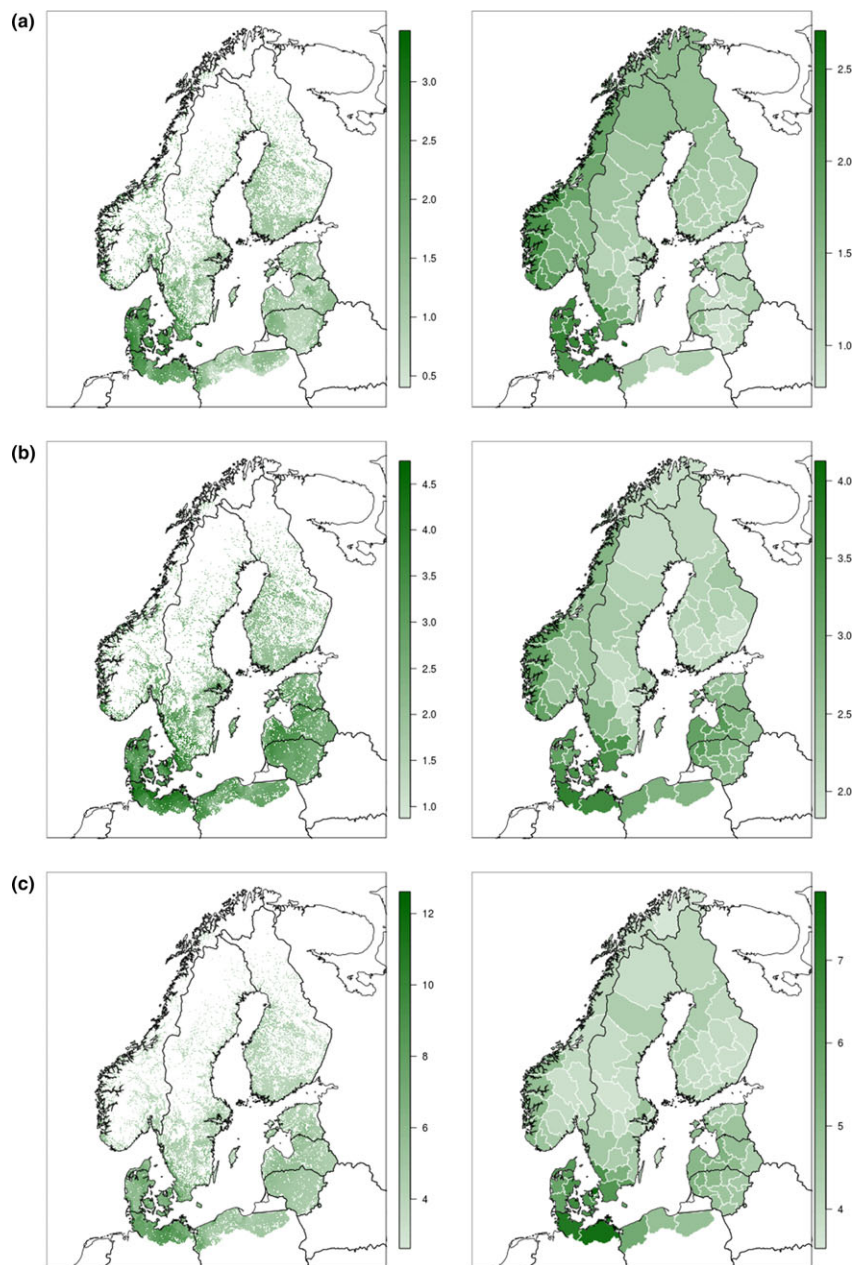


Fig. 6 Yield estimates for willow plantations in the agricultural areas of northern Europe. Darker colours indicate high productivity areas. (a) Lowest performance, (b) middle performance, (c) highest performance group. Left, estimates at 1×1 km resolution (see Supporting Information). Right, averages by regions. The average includes predictions only on agricultural land. Therefore, predictions in the northern latitudes are based on the limited amount of land available.

2011a,b). This data pool presents a realistic basis for yield estimates, as the predictions relate to the final amount of biomass that will be effectively utilized; for example, Sevel *et al.* (2012) estimated differences between nondestructive and harvested observations to be around $1.2 \text{ odt ha}^{-1} \text{ yr}^{-1}$, and Searle & Malins (2014) and Mola-Yudego *et al.* (2015) observed that records from, for example, experimental trials tend to overesti-

mate yields especially when the plots are small. The large amount of data available allowed the inclusion of almost 60% of the whole area planted with willow for bioenergy in Sweden, which enhances the reliability of the estimates.

Nevertheless, a disadvantage of the data used was the lack of detailed information concerning the management practices performed by the farmers, as well as

specific soil records from the plantations. Although some authors have considered that at large, temperature and precipitation are the most important factors for the growth of willow plantations (e.g., Perttu, 1983, 1999), several studies have been demonstrating the important role than soil type, in addition to climate, plays in yield performance (Aylott *et al.*, 2008). In this line, Sevel *et al.* (2012) and Larsen *et al.* (2014) pointed out that soil, clone and its interaction are key variables to model the productivity of willow plantations. In this study, the explicit inclusion of soil variables presented several inconveniences as there is limited information available concerning the soil textures with the necessary spatial resolution and continuity to be included in the models for the studied countries. Similarly, the varieties used in the plantations play an important role in their yield performance (e.g., Lindegaard *et al.*, 2001) but detailed information concerning the clones planted in most of the plantations was also not available.

The aggregation of the plantations in three performance categories, following Mola-Yudego (2010), was aimed at homogenizing the conditions inside the same group, thus incorporating to a certain extent management or local soil conditions. The municipality boundaries were used as a grouping factor, to allow a sufficient number of plantations to make the classification while at the same time assuring that the same climatic conditions would be shared between categories. In this sense, the high performing plantations inside a municipality would most likely be the result of better management, better clones and better soil conditions than the lower performing ones. It must be stressed that farmers decide the location of the plantations and the soil quality where they are established (Mola-Yudego & Aronsson, 2008). The working assumption proposed that the variability between categories may be attributed to variables related to the intensity of management (among others fertilization and rotation length), the local soil quality, the clone used and the interactions of these factors, whereas the climatic variables would rather explain the spatial variability of yields in plantations of the same category. In fact, the performance of the models was lower in the high performance category, underlining the fact that a large part of the variability between plantations in this category was explained by variables other than climate ($R^2 = 0.45$ for the final model), whereas for medium performance category, a

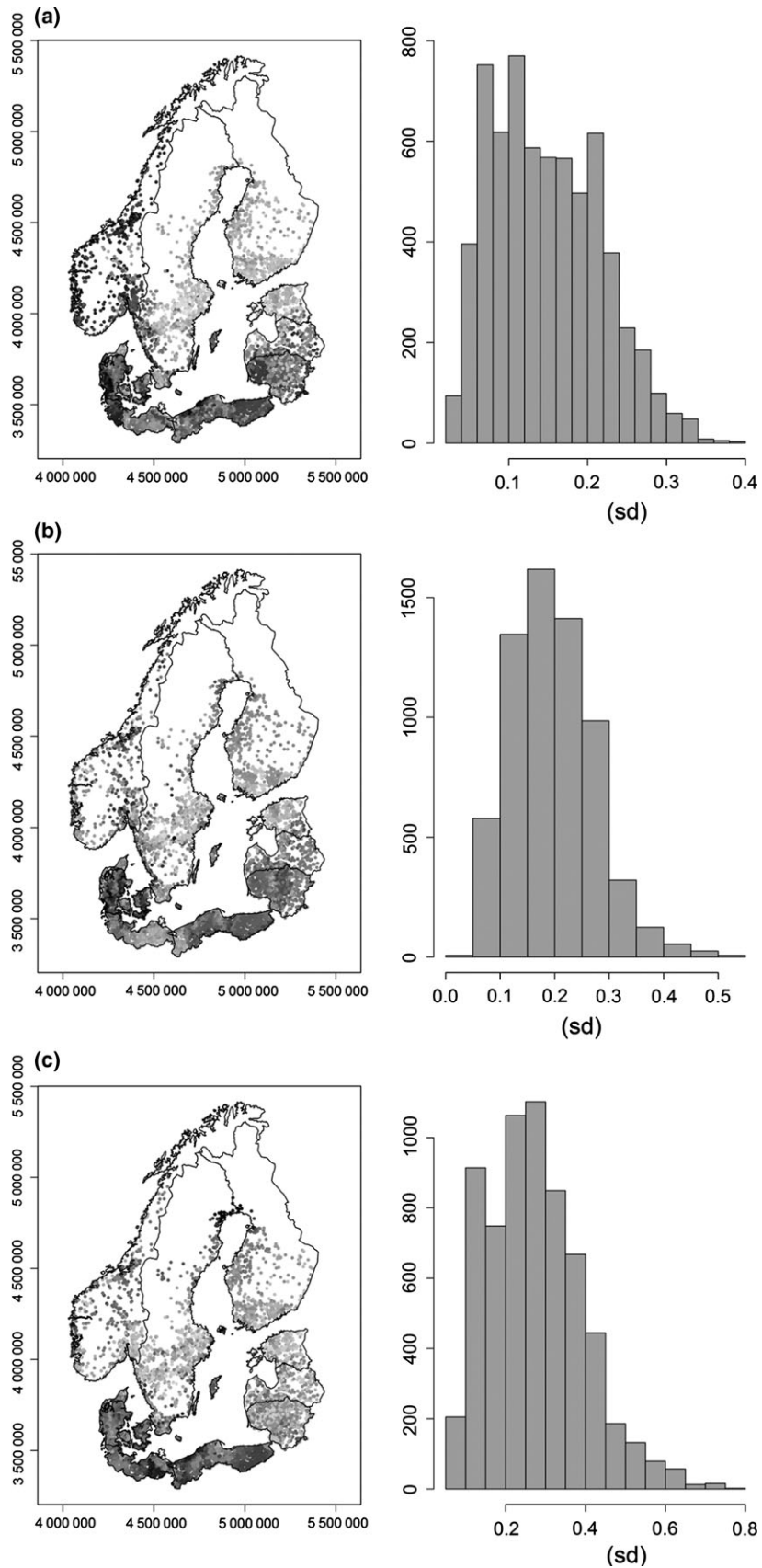
large part of the variability was effectively explained by the variables included ($R^2 = 0.88$). It must be taken into account that it is an *ad hoc* characterization based on final performance, and other factors may have affected yield (e.g., early frosts, heavy rains or moose browsing, among others).

Moreover, yield levels are not fixed and can be increased along time through new varieties and management techniques (Mola-Yudego, 2011b), thus to make a proper use of the predictions provided, they should be taken as a reference threshold defined by climate for the period studied, rather than final predictions. In this sense, the models presented can be recalibrated once new data are available or can be treated as a value based on climate that could incorporate both soil or clone factors by adding scenarios, correction factors in specific areas or an improvement factor based on trends (e.g., Mola-Yudego, 2010).

Several initial studies have modeled the yields in Sweden based on climatic variables (e.g., Nilsson & Eckersten, 1983). Lindroth & B  th (1999) proposed a semimechanistic model to calculate plantations' yield as a linear function of precipitation during the growing season. The application of the model provided maps of potential productivity for central and southern Sweden, but one disadvantage was that the models resulted in higher yield expectations than shown by empirical measurements based on the same commercial plantations (Mola-Yudego & Aronsson, 2008; Mola-Yudego, 2010) and that the method did not offer flexibility as the relationship between precipitation and yield was set to be linear.

The modeling approach taken in this study presents several advantages for modeling climatic data that may overcome these limitations. The use of BRT allows shaping the relationship between the variables and yield with almost no pre-assumptions concerning the shape of the relationship between the variables. This is a great advantage, as some of the variables and their interactions may have thresholds or limiting maxima. At the same time, BRT allows the inclusion of a large number of interactions between the variables and aims at finding those more statistically relevant, simplifying the modeling assumptions taken *a priori*. The approach has recently been used in productivity studies, to, for example, map the site index for different forest species (Aertsens *et al.*, 2010) or the biomass yield of seminatural systems (Van Meerbeek *et al.*, 2014).

Fig. 7 Model sensitivity to changes in the calibration, spatially (left) and by frequency (right). Each point represents the standard deviation (SD) of the predictions resulting from the pool of models. Categories: (a) Lowest performance ($n = 142$ models), (b) middle performance ($n = 135$), (c) highest performance category ($n = 93$). There are 6500 predictions randomly distributed in agricultural land.



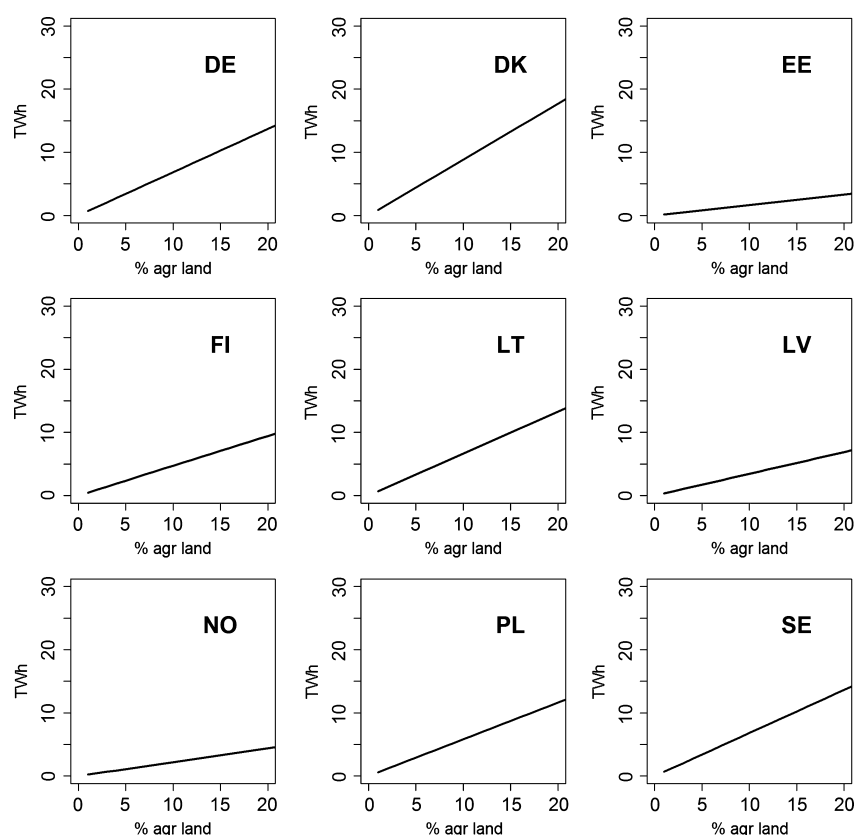


Fig. 8 Estimates for energy production assuming several percentages of available arable land (% agr land) for fast growing willow plantations, with regional average yields under high performance conditions. DE: northern regions (Schleswig-Holstein and Mecklenburg-Vorpommern), PL: northern regions (Warmińsko Mazurskie, Województwo pomorskie and Zachodniopomorskie). DK: referred to 2012, the rest referred to 2013. NO: cultivated land, Statistics Norway (2013). The yield is estimated harvestable biomass during the whole lifespan of a plantation, including one initial year for cut-back and assuming high performance plantations established along the country.

In addition to its predictive power, the method is suitable for interpretation. The results showed that there was a strong effect of precipitation and temperature during early summer, which was expected and is in line with previous work (Lindroth & Båth, 1999). The minimum temperature in October had a strong and positive effect as it was found in Finland in Tahvanainen & Rytkönen (1999). The negative effects of the maximum temperatures in July may be related to higher evapotranspiration and shortage of rainfall, given the high water demands of willow (Linderson *et al.*, 2007).

The models improved existing literature from commercial plantations, with higher prediction power than other studies with the same data (e.g., Mola-Yudego, 2010, 2011a,b), while at the same time being able to deliver high resolution estimates at 1×1 km, although it was observed that the BRT models had problems predicting values in the highest ranges, underestimating the most productive plantations. In general, the averages agreed with previous studies based on commercial

data: In Denmark, the averages found for the best performance category ($6.5 \text{ odt ha}^{-1} \text{ yr}^{-1}$) agree with the estimates of Sevel *et al.*, 2012 ($5.2\text{--}8.8 \text{ odt ha}^{-1} \text{ yr}^{-1}$). In Sweden, the average and spatial estimates were matching the same spatial pattern Mola-Yudego (2011a,b) which used the same data set but with a kNN approach. In this case, the estimates are lower than in Mola-Yudego (2010) as the method could not incorporate the trends due to yield improvements along time. In Finland, the average was similar to Tahvanainen & Rytkönen (1999), although their study referred to standing biomass by nondestructive methods.

The predictions were based on the first harvest, and once plants have developed a root system the following harvests are substantially higher, which is confirmed in the literature (Hoffmann-Schielle, 1995; Labrecque & Teodorescu, 2003; Nordh, 2005). In this study, the average yield for the whole life span of the plantations was estimated using the predicted yield of the first rotation as reference value and then extrapolated using the

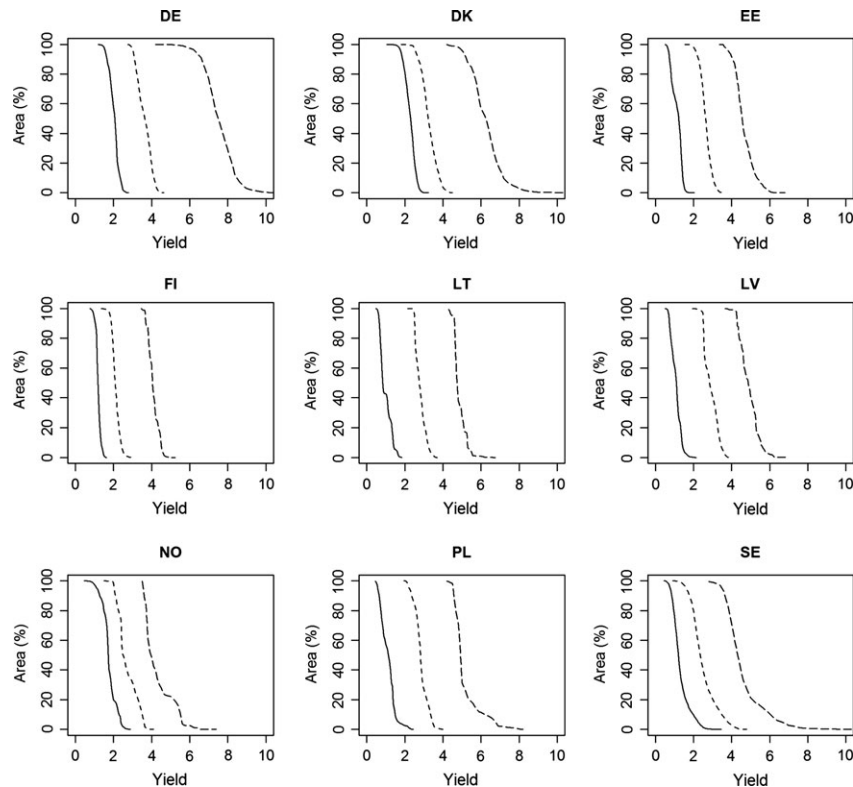


Fig. 9 Areas and potential productivity of short rotation willow plantations on agricultural land in the Nordic area. The areas are presented aggregated under different productivity values, for the low, medium and high performance groups, according to the estimations.

results of Mola-Yudego & Aronsson (2008) and Mola-Yudego (2011b). However, future research must be addressed to study the climatic effects during an extended period, including the specific effects that the climatic variables may have during the second and subsequent rotations. Also, it must be noticed that the final calculation of the whole life span included the first year (*cutback*) which slightly reduced the average yield.

Concerning the spatial accuracy of the predictions, the method applied can present the risk of overfitting when the models become too complex. One of the solutions was the inclusion of a source of stochasticity in the cross-validation used to assess and fit the parameters (Schonlau, 2005) and the use of random points helped to assess the stability of the predictions. The main goal was that, if the parameters used in the models are slightly changed, the resulting predictions should be consistent. The analysis of this spatial consistency showed that the west areas of Jutland in Denmark, as well as the west part of Lithuania and Latvia, and some areas in Poland are particularly sensitive to the calibration parameters and indicate that the yield extrapolation based solely on climatic variables and data from Swe-

den may need additional data for a proper calibration, perhaps related to soil conditions in the area.

The predictions were restricted to agricultural land, and the regional averages were therefore based on predictions for these areas (i.e., excluding forest lands, non-productive land, lakes and rivers). This resulted in high regional values for northernmost areas (e.g., Lapland, Norrlands or Finnmark). As agriculture land is scarce on northern latitudes and located mainly in favorable conditions nearby the coast, the resulting averages for those counties are high as are based in a small sample distributed unevenly. Although those northern areas, in general, present the most adverse climatic conditions to willow establishment, attempts to develop highly productive clones with frost tolerance for those areas have been done since the late 1980s (Lumme & Törmälä, 1988), and relatively high yields cannot be excluded as a future scenario.

Finally, the country estimates considered the energy produced under different percentages of agricultural land up to 30%, for reference. It is difficult to estimate for the whole region the area that will eventually be dedicated to fast-growing plantations for energy. As a

reference, however, Aust *et al.* (2014) suggested that considering all ecological, ethical, political and technical restrictions, as well as future climate predictions, 5.7% of cropland would be a suitable percentage for Germany.

The area studied shares many climatic and geographical features with the areas in Sweden already cultivated with fast-growing plantations. In fact, for most of Denmark and the west and southernmost cultivation zones in Finland, the Swedish experience concerning willow varieties and methods can probably be directly transferred. In the case of Norway, there is good potential in many parts of the country. Despite the country's overall limitations in agricultural land, areas located in the Østfold and Akerhus present good conditions for the establishment of plantation schemes: the results show high potential yields, share geographical proximity and climatic similarity with Sweden allowing the interchange of varieties, there is agricultural land available (c. 16% of the land, Statistics Norway, 2013), and there is a potential demand of wood chips for bioenergy due to the high density of population. In the Baltic countries and Baltic coast of Poland and Germany, the results show good potential yields that can translate into significant figures of energy production. Additionally, the enlargement of cultivated areas in those zones can result in rapid yield improvements once a critical market size is reached (Mola-Yudego *et al.*, 2014).

Indicatively, in the case of Sweden, estimates show that 1% and 5% of agricultural land could translate into 1.5% and 7.2% of the total annual heat consumption, respectively (annual heat estimated in 47 TWh, Swedish Energy Agency, 2013). However, there are several components of potential supply of biomass crops beyond yield estimation that can play an important role in developing the potential supply (e.g., the current agricultural systems, the role of relative prices, input costs and policy developments) and must be taken into account.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Figure S1. Yield estimates based on climatic variables at 1 × 1 km resolution for willow plantations on agricultural areas of northern Europe for a lowest performance scenario.

Figure S2. Yield estimates based on climatic variables at 1 × 1 km resolution for willow plantations on agricultural areas of northern Europe for a middle performance scenario.

Figure S3. Yield estimates based on climatic variables at 1 × 1 km resolution for willow plantations on agricultural areas of northern Europe for a highest performance scenario.

Appendix S1. Average yield response (marginal effect) by climatic variable.